Multi-frequency electrical impedance analysis for monitoring aqueous solutions using an accelerated neural network approach

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Abstract: *Machine learning models are hungry for data, providing this large amount of data while still conserving a compact setup is a major challenge. Integrating an accelerated hardware Neural Network together with the sensor data used as input nodes for the model will result in a compact and low-power device capable of edge-processing a supervised Convolutional Neural Network.*

Introduction

Electrical Impedance Spectrum (EIS) is a technique that is becoming more popular when looking for a cheap, compact, quick and non-invasive way to measure. This technique uses a range of frequencies over which a sample is measured, every frequency contains their own features which is based on a different flow of currents. Having this amount of information at your disposal, processing it becomes a major challenge. However, when looking into the artificial intelligence research branch, techniques can be derived to process this data resulting into a more compact form factor of the same data with the benefit of using this derived data to classify, or even predict reoccurring patterns.

Numerous applications can benefit from this technique. As a first example, Cleaning In Place (CIP) is taken. CIP is a generalized term for all mechanical and chemical systems that are required in the food processing industry to clean industrial processing lines[1]. Other examples include quality control of milk and multi-sensor systems replacing human senses[2]. These examples prove combining impedance data with machine learning models result in a successful outcome regarding data predictions.

Material and Methods

By measuring the fluids inline, a high throughput is conserved which is beneficial to generate larger datasets. Under a constant flow, the impedance spectrum together with the temperature is logged which in their turn are used as input for the neural network. This gives us a frequency spectrum of 100 Hz - 10 kHz and a temperature signal both in function of time. However before this can be done the data first needs to be labelled, filtered, trimmed, synchronized and resampled.

As a test-setup, three fluids are introduced: milk, orange juice and NaOH as the cleaning fluid. Measuring the impedance and temperature of these fluids over time result in a dataset appropriate to be used as training data for a machine learning model.

The data has been subjected to a couple of filtering techniques such as a moving average filter, synchronisation, data shifting and interpolation. The data is finally saved as a matrix of 170 x 38 x 7. Meaning the dataset consist out of 170 independent measurements in time, this for 38 samples and done for 7 signals coming from the 2 earlier mentioned measurements.

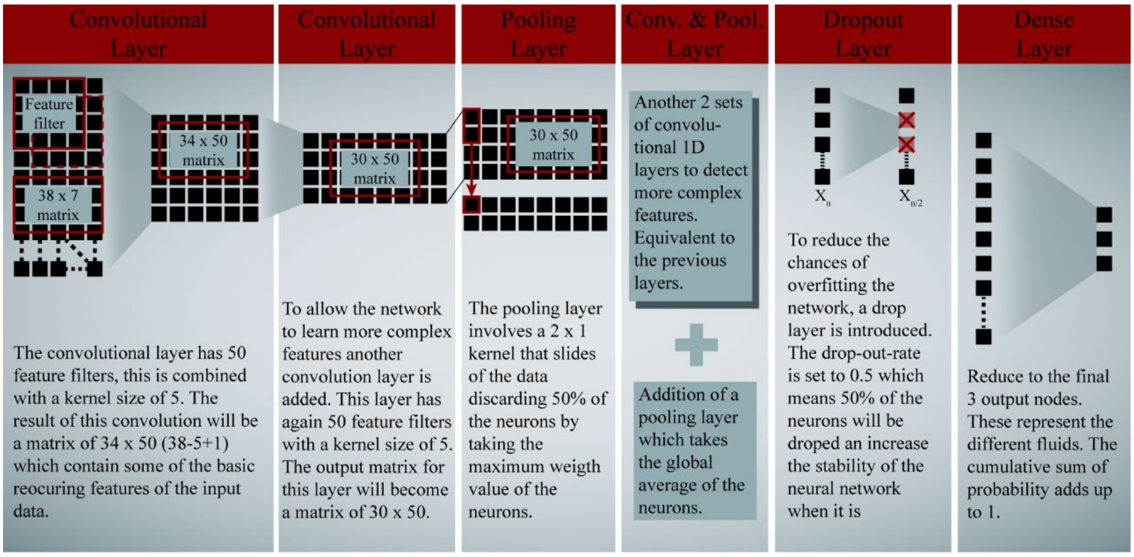

Figure 1: brief summary of the convolutional neural network. The model includes 7 hidden layer, this combined with the input and output layer adds up to a total of 9 layers. Using this model an accuracy of 84% was reached.

The neural network consist in total out of 9 layers, this includes the input and output layer. In the end the output layer of 3 nodes will give an indication on how will the neural network interpret the previously unknown data.

Results and Discussion

In the training data, an accuracy of 99% was achieved, and the validation data showed an accuracy of 80%. After creating the model it was subjected to classify a dataset of independent measurements to verify the accuracy, this resulted in an accuracy of 84%. The last value can be accepted as the general accuracy of the system, this because it gives an indication on how well the model performs on actual data that previously was unknown for the model.

In recent years machine learning studies are done on a variety of datasets, examples ranging from speech recognition, image labelling, real-time predictions and in some cases the algorithms outperformed humans[3]. This proofs an artificially intelligent system can be used to distinguish fluids in real-time.

Conclusions

At this moment the accuracy of the model is limited to 84%, this can be still be improved. A bigger dataset will decrease the impact factor of a badly labelled measurement significantly, so as a direct result to this an increase in accuracy is expected.

References

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